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Energy-Efficient Multi-Level Collaborative Optimization for Robotic Manufacturing Systems

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Abstract

Aiming at the multi-level hierarchy framework of robotic manufacturing systems, how to realize a comprehensive energy-efficient optimization of the whole system is crucial to realize the sustainability of manufacturing. In this paper, the production-process oriented physical energy consumption model and digital model of industrial robots together with their interaction mechanisms are studied. Then, the concurrent assessment and evolution prediction approaches of robotic manufacturing systems are presented, as well as the collaborative optimization method based on knowledge evolution. Finally, a case study is implemented to verify the effectiveness of the proposed method.

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Keywords: robotic manufacturing systems, multi-level hierarchy framework, energy-efficient, collaborative optimization ;

1. Introduction

Energy consumption is the key indicator of sustainable manufacturing. According to the statistics, the manufacturing industry almost accounts for 90% energy consumption of the whole industrial sector [1]. In order to take both the economic benefits of enterprises and the environmental protection into consideration, how to obtain the optimal energy consumption during the production processes has been an important issue in academia and industry. The energy-efficient manufacturing model which focusing on both production efficiency and energy consumption has been developed in [2]. On the other hand, since the industrial robots (IRs) have been widely used in intelligent manufacturing and its energy consumption proportion is significantly increasing, optimizing the energy consumption of IRs has become an important issue for robotic manufacturing systems (RMSs).

Industrial robot is an important manufacturing equipment in the production process of job shop, and has the characteristics of high repetition accuracy, adaptability and flexibility under harsh working conditions. With the rapid development of cyber-physical production system (CPPS) [3, 4], IRs together with the advanced sensor technology, control technology, artificial intelligence have been widely used in various manufacturing industries, such as automobile, aerospace, ship, etc. Meanwhile, the energy consumption of IRs has been paid increasing attention by academia and industry. For instance, in automobile manufacturing, the electricity power consumed by IRs is almost 8% of the entire energy consumption in production process. For IRs, there is 20%~40% energy consumption need to be further reduced [5]. As we know, RMSs in factory floor environment is multi-level hierarchy framework which consists of manufacturing cell level and production line level. Therefore, this paper studies the energy consumption mechanism, the production evolution process and the energy-efficient optimization of RMSs. After that, corresponding enabling technologies are studied.

2. Related work

In the factory floor environment, the way to improve the energy efficiency of RMSs can be divided into two levels

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which includes manufacturing cell level and production line level. In manufacturing cell level, energy consumption of IRs can be reduced from the aspects of energy temporary storage and recovery, DC power supply system, braking state management, trajectory optimization, etc. [5, 6]. On the other hand, in production line level, the production scheduling and process control of IRs can be optimized by production line design optimization and production line scheduling [7, 8].

For the physical energy consumption model of IRs, there are many researches focus on the dynamic parameter identification of industrial robot. The kinetic parameters were estimated by the least squares estimation or maximum likelihood estimation, relying on the measured position and torque of the joints [9]. For the modeling of joint friction, Stribeck model was used to describe the low-speed and high-speed characteristics of relative motion surface friction [10].

For the digital description and modeling of IRs, based on the core ontology for robotics and automation (CORA), ontology model of industrial assembly robot capacity can be constructed. The digital description of industrial robot structure, assembly action, actuator and other information were realized [11]. The Virtual Reality Training System was also proposed to enable the real-time simulation of industrial robot manipulators and human collaboration to finish manufacturing tasks [12].

For the assessment of operating process of IRs, a method which evaluates the manufacturing capacity of various IRs from load capacity, repeatability error, operating range, maximum end speed and other indicators was presented in [10]. Combing the subjective and objective assessment, the weights of indicators were determined by fuzzy hierarchical analysis and the optimization scheme of robot was determined by the running data during the certain time [13].

The energy consumption of IRs in operating process is affected by both the electrical characteristics and the mechanical characteristics. It is closely related to the kinematic parameters and the operation control. In addition, the scheduling of a production line has direct effect on the energy-efficient performance of IRs in manufacturing systems. In the manufacturing cell level, the different operations of IRs as well as the energy consumption characteristics under different operation parameters, such as load, speed, acceleration, etc. were analyzed to support the operation control optimization [6]. In the production line level, aiming at the reduction of production time and energy consumption, scheduling method was developed based on the trajectory planning of IRs in the manufacturing systems [8]. The detailed energy-efficient optimization methods were discussed in [14-16].

From the aforementioned analysis, it can be seen that there is limited research which considers the operation optimization of RMSs from a view of multi-level hierarchy framework, as well as the evolution characteristic of each level and the interactive relationships. Moreover, the complexity, dynamics and uncertainties of RMSs operating in the production process are still the challenge to realize comprehensive optimization of such manufacturing systems in factory floor environment.

3. Requirements and framework

The operation mechanism of RMSs in factory floor environment is illustrated in Fig. 1. RMSs have a multi-level hierarchy framework which includes production line level and manufacturing cell level. The relationships between the two levels, the operation and energy consumption characteristics are described in the following aspects:

(1) The heterogeneity, complexity, and dynamics of IRs. The various functionalities and different structures of IRs make the energy consumption mechanism complex. The servo drive system of industrial robot includes the electrical and mechanical parts. The kinetic parameters are complex, and the multi-joints of a robot are coupled. The different operating status such as stopping, braking, etc. in the production process also make the energy consumption of IR highly dynamic.

(2) The complexity, dynamics, and uncertainty of IRs operating in production process. The IRs can be applied in various manufacturing tasks and the requirements are different, thus the process planning and scheduling of RMSs are usually complicated. The change of manufacturing tasks requires that IRs can make dynamical adjustments in the production process. Moreover, when the production environment changes, fluctuation of product quality, manufacturing equipment degradation, and other factors can also make the production process and the energy consumption of RMSs highly uncertain.

(3) The interactive relationships between multi-levels in the hierarchy framework of RMSs. In the RMSs, the adjustments of manufacturing cells can affect the operation performance of whole production line. The process planning and scheduling in the production line level also require the manufacturing cell equipment can make timely adjustments. The operations of IRs in the two levels have close interactive relationships. Therefore, the operation optimization of RMSs at any level can directly affect the other level.

4. Mechanism and approach

To realize comprehensive operation optimization of RMSs, we should consider the operation mechanism of different levels in the hierarchy framework. It also needs to develop approaches to conquer the complexity, dynamics and uncertainty of the whole manufacturing system. Inspire from successful implementation of CPPS, we firstly establish the physical energy consumption model and the digital model of IRs, and realize the correlation and intergrowth of the two type models. Based on this, the concurrent assessment and evolution prediction approach are developed to reveal the dynamic energy-efficient operation performance of RMSs. Finally, the collaborative optimization approach based on the knowledge evolution driven by physical model is developed.

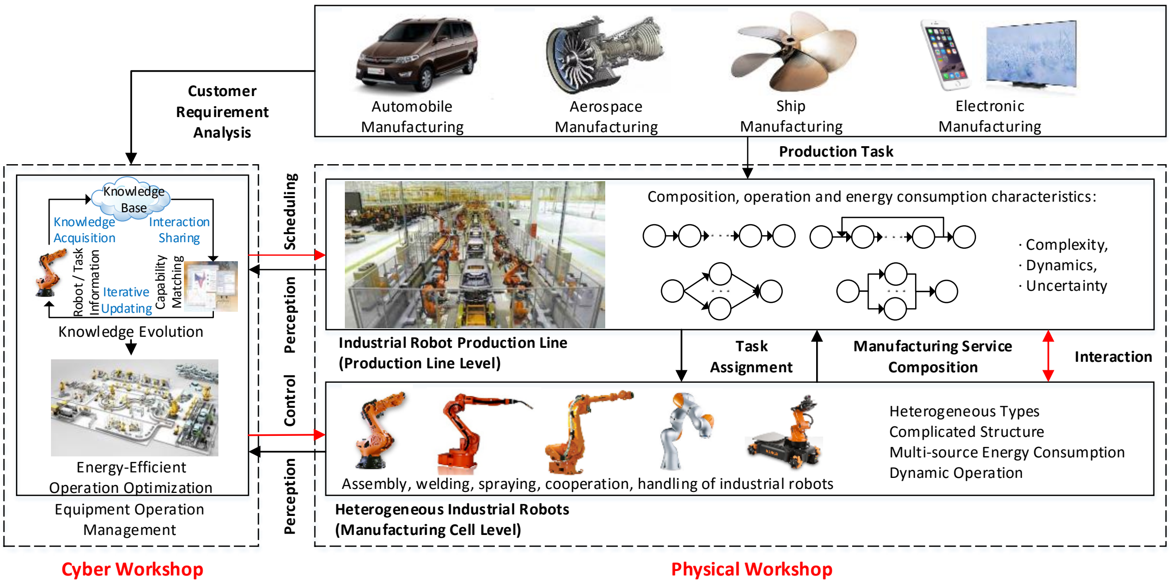

Fig. 1. The operation mechanism of IRs in RMSs.

4.1. Physical energy consumption modeling

The physical basis to realize the energy-efficient multi-level optimization of IRs is to understand the energy consumption formation mechanism, clarify the factors that promote the generation and change of energy consumption, and reveal the relationships among the energy consumption, the operating status and the production task conditions of the RMSs. Therefore, the analysis of multi-source energy consumption formation mechanism based on the measurement data should be studied.

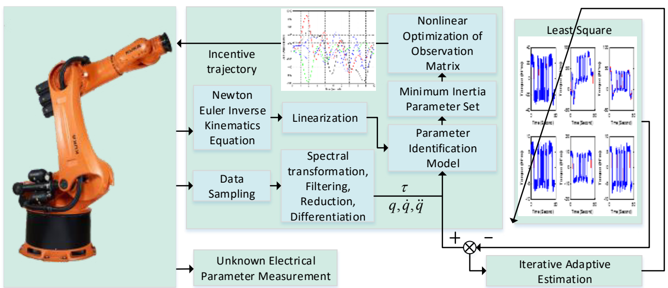

Fig. 2. The dynamic energy consumption model of the IRs based on parameter identification.

The energy consumption data which includes the electrical energy consumption, the mechanical energy consumption, and the energy consumption of auxiliary equipment can be obtained by statistical analysis of external energy consumption measurement and the on-line data obtained by robot controller, together with the related electrical and dynamics theories. The classification and feature extraction of measurement data makes it possible to grasp the energy consumption behavior and formation mechanism of IRs. Meanwhile, the mathematical characterization and analysis of multi-source energy consumption of IRs can also be realized based on the physics-based theories.

Multi-source energy consumption formation mechanism is the basis of dynamic energy consumption modeling of IRs [17, 18]. The kinetic parameters related to the energy consumption of IRs can be obtained by physical parameter identification based on measurement data [19]. Combining with the mathematical model of dynamic energy consumption sources, the dynamic energy consumption modeling based on the physical parameter identification are described in Fig. 2.

In addition, the physical energy consumption model of the IRs towards the manufacturing process is also required to understand the energy characteristics of RMSs in production process. It is necessary to reveal the interactive relationships among the multiple energy consumption sources, the operation status of IRs and the task conditions of RMSs in production process. Meanwhile, it is also required to establish the mapping relationships between the running element status of manufacturing cell and the multiple energy consumption sources. Based on the aforementioned methods, the physical energy consumption model can be established and reveal the energy consumption mechanism and transmission rule of RMSs. It can also effectively trace the dynamics and uncertainty in the production process in both levels.

4.2. Energy-efficient digital modeling

The digital modeling of IRs is the knowledge basis for supporting the energy-efficient optimization of RMSs in production process. At present, there is still limited research focuses on realizing the unified and dynamic knowledge description of heterogeneous IRs considering the multi-level of RMSs.

In order to conquer the aforementioned limitations, the energy-efficient unified digital description mechanism of IRs towards multi-level hierarchy framework should be studied. As shown in Fig. 3, based on the physical energy consumption model, it is required to establish cognitive semantic and scalable unified description framework for IRs by mining the knowledge concepts, attributes, logic constraints and axioms rules related to the production capability and energy consumption performance in both levels of RMSs.

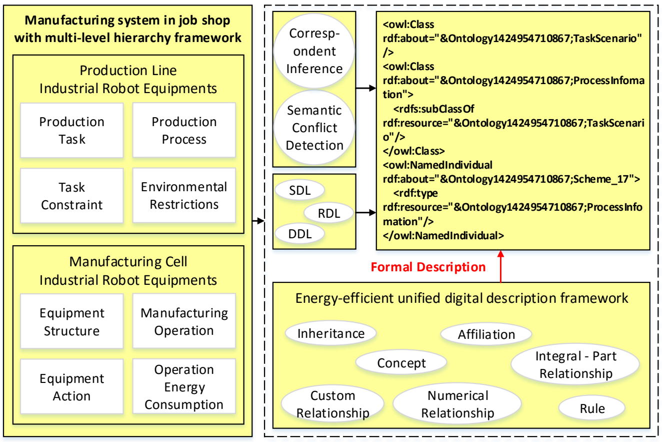

Fig. 3. The energy-efficient unified digital description mechanism of the RMSs toward multi-level hierarchy framework.

After the realization of energy-efficient unified digital description, the dynamic digital description model of IRs driven by physical model should be developed. Due to the dynamics and uncertainty of RMSs in production process, to establish the multi-level description network model, it is required to analyze the dynamic characteristics of multi-level network topology, differences of network characteristics driven by physical model. It also needs to study the evolution rules of the multi-level description network model. Digital twin technology [20-22] is able to provide feasible and effective way to realize the correlation and intergrowth of the digital models and the physical models of RMSs. It can facilitate the digital models trace the complexity, dynamics and uncertainty of RMSs in production process.

4.3. Energy-efficient concurrent assessment and evolution prediction

The operation performance assessment and evolution prediction are the decision-making basis to deal with the interactive relationships between both levels. Aiming at characteristics of multi-level hierarchy framework of RMSs, it is necessary to develop comprehensive energy-efficient assessment indicators and the multi-dimensional assessment criterions. It also needs to establish the mapping relationships among different multi-level performance indicators. The energy-efficient concurrent assessment model based on statistical characterization correlation analysis is shown in Fig. 4, together with the dynamic correction mechanism of assessment model by using the feedback operation data.

The multi-source energy consumption data related to the production process is the knowledge basis for the concurrent assessment and evolution prediction of RMSs, the energy-efficient dynamic assessment method driven by multi-source data fusion under multi-level hierarchy framework of RMSs should be developed. The adaptive weighted fusion calculation and feature data extraction strategy are also required to facilitate the assessment method to meet the requirements of dynamics and uncertainty of RMSs in production process. In addition, in order to realize dynamic adjustment of assessment method, according to error feedback information, the assessment error can be calculated by means of quantitative methods [23] at both levels of RMSs.

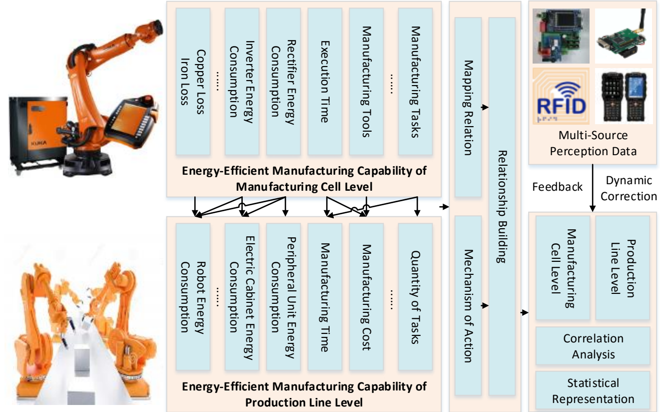

Fig. 4. The energy-efficient concurrent assessment model.

Based on the various timing data and assessment data obtained in the production process of RMSs, approaches such as Markov chain [24] can be used to obtain the intensity transfer probability matrix and excavate the energy-efficient time-varying evolution rules for operations of IRs to realize evolution prediction of RMSs in production process.

4.4. Energy-efficient multi-level collaborative optimization

Currently, in factory floor environment, the existing optimization methods seldom consider the interactive relationships between manufacturing cell level and production line level to achieve comprehensive performance improvement of the whole manufacturing system. Meanwhile, the aforementioned enabling approaches, such as the physical energy consumption model, the energy-efficient digital model and the energy-efficient concurrent assessment and evolution prediction should be used together to facilitate the dynamic optimization of RMSs from the whole system view. It can also deal with the system disturbance caused by dynamics and uncertainty in the production process.

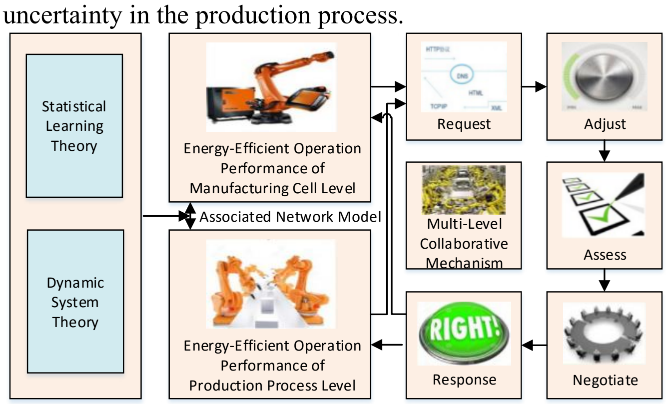

Fig. 5. The energy-efficient multi-level collaborative optimization model.

In [25], the cross-layer optimization model has been developed to show the interactive mechanisms of RMSs. Based on the dynamic system theory and statistical learning theory, the data interaction and information sharing strategy between both levels should be studied. Besides, the data transmission criteria, the multi-level information interactive and sharing mechanism should also be developed. The collaborative optimization mechanism ('request - adjust - assess - negotiate - response' interactive strategy) is described in Fig. 5.

The existing optimization methods are not suitable to realize comprehensive optimization problem of the multi-level hierarchy framework of RMSs in factory floor environment. Under this condition, self-learning knowledge evolution mechanism should be used to realize adaptive optimization in such system. By the idea of 'data drive - knowledge extraction - knowledge evolution', the deep learning mining method used for the energy-efficient optimization feature knowledge can be developed. Furthermore, considering the constraints of decision-making time in production process, we can determine the proper interactive trial and error assessment to obtain the optimal decision-making knowledge within limited time. The knowledge evolution mechanism of the energy-efficient optimization can be driven by the data obtained by the developed physical model.

Combining with the multi-level collaborative optimization model and the self-learning knowledge evolution mechanism, the comprehensive energy-efficient optimization approach can be realized by jointly implementation of optimized operation control of IRs in the manufacturing cell and the optimized process planning and scheduling in the production line.

5. Case study and Implementation

In order to verify the effectiveness of proposed framework, theories and approaches for RMSs, a simple vehicle body assembly case in industrial robotic assembly is illustrated in this section. This assembly line has 7 types of processes, including the frame assembly, the wheel assembly, the engine assembly, the instrument assembly, the brake assembly, the components assembly and the vehicle assembly. It means there are 7 types of industrial robot manufacturing capability services in the manufacturing cell level. The energy-efficient optimization of RMSs is to obtain the maximum QoS and the minimum energy consumption (En) within the optimum tradeoff. Here, En, four generic QoS attributes which includes the response time (T), execution cost (C), availability (A) and reliability (R), are used to evaluate the availability and effectiveness of energy-efficient multi-level collaborative optimization of RMSs. T and C are considered as two objectives which conflict with each other. A and R are the constraints. The weighted QoS (WQoS) and EnQoS of the assembly process are defined by Eqs. (1) and (2) respectively. EnQoS(cs) represents capability which considering both En and WQoS in the specific composition service (cs). α, β are the weights of assessment of composition service quality.

$$WQoS(cs) = \alpha T(cs) + \beta C(cs) \quad (1)$$

$$EnQoS(cs) = \min(En(cs)) \,\&\, \min(WQoS(cs)) \quad (2)$$

Based on MATLAB, the results of WQoS, EnQoS and performance comparisons between situations A and B achieved by the simulation methods [25, 26] are respectively shown in Fig. 6, Fig. 7, and Table 1. The situation B is the optimization result obtained by considering the EEMLCO mechanism while the situation A is the optimization result without considering the EEMLCO mechanism.

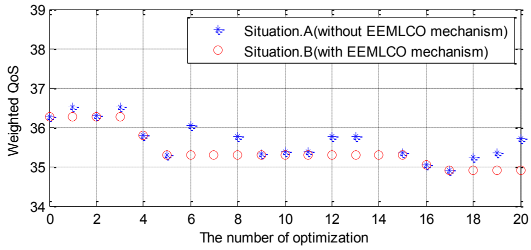

Fig. 6. The WQoS of both the optimization situations.

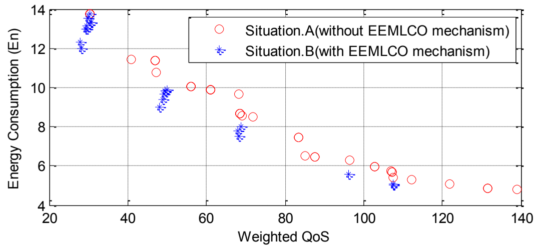

Fig. 7. The EnQoS distribution of both the optimization situations.

Table 1. The performance comparisons between QoS(A) and QoS(B).

Number of optimization	Number of $QoS(A) \prec QoS(B)$	Number of $QoS(A) \succ QoS(B)$	Number of $QoS(A) \prec\!\succ QoS(B)$
20	0	16	4
50	1	32	17
100	3	65	32
200	8	117	75

From the Fig. 6, it is obvious the situation B is better than the situation A in terms of WQoS. In addition, it is obvious that QoS(B) dominates QoS(A) in most cases in Table 1. Fig. 7 indicates that when the number of optimization is 40, there are a number of $EnQoS_B(cs)$ Pareto dominate $EnQoS_A(cs)$, and no $EnQoS_A(cs)$ Pareto dominates $EnQoS_B(cs)$. Thus, by considering EEMLCO mechanism, both QoS and En are better than the results without considering EEMLCO mechanism.

6. Conclusion

In this paper, multi-level hierarchy optimization framework for RMSs is developed to realize comprehensive energy-efficient performance improvement. Moreover, to facilitate the implementation of proposed framework, the enabling mechanisms and approaches which include the physical energy consumption modeling, digital modeling of IRs towards the production process, the concurrent assessment and evolution prediction approaches and the collaborative optimization method based on knowledge evolution are presented. Case study demonstrates the energy-efficient performance of the whole manufacturing system can be significantly improved when EEMLCO mechanism is adopted. The developed multi-level hierarchy framework can also be used in the prognostics and health management. We will also finish more detailed researches in this area in the future.

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References

[1] Zhou Z, Yao B, Xu W, Wang L. Condition monitoring towards energy-efficient manufacturing: a review. International Journal of Advanced Manufacturing Technology, 2017;91(9-12):1-21.

[2] Duflou J R, Sutherland J W, Dornfeld D, et al. Towards energy and resource efficient manufacturing: A processes and systems approach. CIRP Annals - Manufacturing Technology, 2012;61(2): 587-609.

[3] Monostori L. Cyber-physical production systems: Roots, expectations and R&D challenges. In: Proceedings of the 47th CIRP Conference on Manufacturing Systems, Procedia CIRP, 2014;17: 9-13.

[4] Wang L, Törngren M, Onori M. Current status and advancement of cyber-physical systems in manufacturing. Journal of Manufacturing Systems, 2015;37(2): 517-527.

[5] Meike D, Pellicciari M, Berselli G. Energy efficient use of multirobot production lines in the automotive industry: Detailed system modeling and optimization. IEEE Transactions on Automation Science and Engineering, 2014;11(3): 798-809.

[6] Paryanto, Brossog M, Bornschlegl M, Franke J. Reducing the energy consumption of industrial robots in manufacturing systems. International Journal of Advanced Manufacturing Technology, 2015;78(5-8): 1315-1328.

[7] Peng T, Xun X. Energy-efficient machining systems: a critical review. International Journal of Advanced Manufacturing Technology, 2014;72(9-12): 1389-1406.

[8] Tao F, Laili Y, Xu L, et al. FC-PACO-RM: A Parallel Method for Service Composition Optimal-Selection in Cloud Manufacturing System. IEEE Transactions on Industrial Informatics, 2013;9(4):2023-2033.

[9] Khandekar A V, Chakraborty S. Selection of industrial robot using axiomatic design principles in fuzzy environment. Decision Science Letters, 2015;4(2):181-192.

[10] Hollerbach J, Khalil W, Gautier M. Model identification. Springer Handbook of Robotics, Springer Berlin Heidelberg. 2008;321-44.

[11] Kootbally Z. Industrial robot capability models for agile manufacturing. Industrial Robot: An International Journal, 2016;43(5): 481-494.

[12] Matsas E, Vosniakos G C. Design of a virtual reality training system for human-robot collaboration in manufacturing tasks. International Journal on Interactive Design and Manufacturing, 2017;11(2): 139-153.

[13] Parameshwaran R, Kumar S P, Saravanakumar K. An integrated fuzzy MCDM based approach for robot selection considering objective and subjective criteria. Applied Soft Computing, 2015;26: 31-41.

[14] Wang L, Wang W, Liu D. Dynamic feature based adaptive process planning for energy-efficient NC machining. CIRP Annals - Manufacturing Technology, 2017;66: 441-444.

[15] Tao F, Bi L, Zuo Y, et al. A. Y. C. Nee. A cooperative co-evolutionary algorithm for large-scale process planning with energy consideration. Journal of Manufacturing Science and Engineering - Transactions of the ASME, 2017;139(6): 061016-061016-11.

[16] Xu W, Shao L, Yao B, et al. Perception data-driven optimization of manufacturing equipment service scheduling in sustainable manufacturing. Journal of Manufacturing Systems, 2016;41: 86-101.

[17] Wang L, Mohammed A, Wang X V, et al. Recent advancements of smart manufacturing: an example of energy-efficient robot. International Conference on Flexible Automation and Intelligent Manufacturing. 2016.

[18] Mohammed A, Schmidt B, Wang L. Energy-efficient robot configuration for assembly. Journal of Manufacturing Science & Engineering, 2017;139(5):051007-051007-7.

[19] Xu W, Liu H, Liu J, et al. A practical energy modeling method for industrial robots in manufacturing. In: the 19th Monterey Workshop, Beijing, China, October 8-11, 2016.

[20] Uhlemann T H J, Lehmann C, Steinhilper R. The digital twin: realizing the cyber-physical production system for Industry 4.0. In: the 24th CIRP Conference on Life Cycle Engineering, Procedia CIRP, 2017;61: 335-340.

[21] Tao F, Cheng J, Qi Q, et al. Digital twin-driven product design, manufacturing and service with big data. The International Journal of Advanced Manufacturing Technology, 2017;94(9-12): 3563–3576.

[22] Zhang Q, Zhang X, Xu W, et al. Modeling of digital twin workshop based on perception data. In: International Conference on Intelligent Robotics and Applications (ICIRA'17), 2017. 3-14.

[23] Zhang Z, Xu W, Liu Q, et al. Dynamic manufacturing capability assessment of industrial robots based on feedback information in cloud manufacturing. In: Proceedings of the ASME 2017 International Manufacturing Science and Engineering Conference (MSEC'17), Los Angeles, CA, USA, June 4-8, 2017.

[24] Hamasha M M, Alazzam A, Hamasha S, et al. Multimachine flexible manufacturing cell analysis using a Markov chain-based approach. IEEE Transactions on Components, Packaging and Manufacturing Technology, 2015;5(3): 439-446.

[25] Zhang J, Liu Q, Xu W, et. al. Cross-layer optimization model toward service-oriented robotic manufacturing systems. ASME. Journal of Manufacturing Science and Engineering. 2018;140(4):041002-041002-7. doi:10.1115/1.4037605.

[26] Xu W, Tian S, Liu Q, et. al. An improved discrete bees algorithm for correlation-aware service aggregation optimization in cloud manufacturing. The International Journal of Advanced Manufacturing Technology, 2016;84: 17-28.